



Vulnerability of forest vegetation to anthropogenic climate change in China

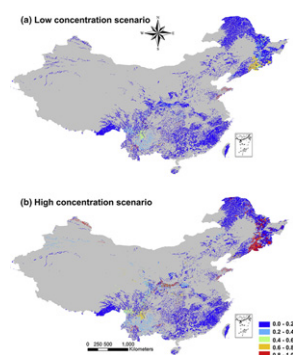
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HIGHLIGHTS

- We examined vulnerability of 204 forest communities across 16 vegetation types under climate change.
- There were large vulnerable areas of forest vegetation in northeastern and southwestern China.
- The vulnerability of forest vegetation may increase due to high greenhouse gas concentrations.
- We should integrate projected climate changes into adaptive conservation strategies for forest vegetation in China.

GRAPHICAL ABSTRACT



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ABSTRACT

China has large areas of forest vegetation that are critical to biodiversity and carbon storage. It is important to assess vulnerability of forest vegetation to anthropogenic climate change in China because it may change the distributions and species compositions of forest vegetation. Based on the equilibrium assumption of forest communities across different spatial and temporal scales, we used species distribution modelling coupled with endemics–area relationship to assess the vulnerability of 204 forest communities across 16 vegetation types under different climate change scenarios in China. By mapping the vulnerability of forest vegetation to climate change, we determined that 78.9% and 61.8% of forest vegetation should be relatively stable in the low and high concentration scenarios, respectively. There were large vulnerable areas of forest vegetation under anthropogenic climate change in northeastern and southwestern China. The vegetation of subtropical mixed broadleaf evergreen and deciduous forest, cold-temperate and temperate mountains needleleaf forest, and temperate mixed needleleaf and broadleaf deciduous forest types were the most vulnerable under climate change. Furthermore, the vulnerability of forest vegetation may increase due to high greenhouse gas concentrations. Given our estimates of forest vegetation vulnerability to anthropogenic climate change, it is critical that we ensure long-term monitoring of forest vegetation responses to future climate change to assess our projections against observations. We need to better integrate projected changes of temperature and precipitation into climate-adaptive conservation strategies for forest vegetation in China.

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1. Introduction

Forests are an important natural resource utilized for economic productivity, wildlife conservation and utilization, and water and soil

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conservation (Dixon et al., 1994; McCarthy and Burgman, 1995; Hanewinkel et al., 2013; Keenan et al., 2013; Gebrehiwot et al., 2014). Forests also hold large stores of carbon that depend on a balance of primary production and ecosystem respiration, processes that respond to climate change (Peng et al., 2009; Hanewinkel et al., 2013; Coomes et al., 2014; Margono et al., 2014; Michaletz et al., 2014; Reyer et al., 2014). Hence, the effective management of forest resources can contribute to forestry and land management, and the conservation of biosphere. Rapid climate change due to human activities has great potential to change the distributions and species composition of forest vegetation, threaten forest ecosystems, and even reduce biodiversity and the availability of ecosystem services (Hanewinkel et al., 2013; Coomes et al., 2014; Buizer et al., 2014; Ripple et al., 2014; Zhu et al., 2014). Such effects may severely threaten the atmosphere and anthroposphere; thus, environmental degradation may increase, resulting in habitat fragmentation or loss for many species (Buizer et al., 2014; Matthews et al., 2014; Hanski, 2015). The shifts of forest vegetation may negatively affect diversity and the adaptive capacity of ecosystems across different scales, from communities to globe (Landres et al., 1999; Chazdon, 2008; Lindner et al., 2010; Tian et al., 2011; Hanewinkel et al., 2013). Global and regional policies that exacerbate biodiversity decline and extinction of forests in the near future pose a great risk for society (Hanewinkel et al., 2013; Buizer et al., 2014; Ripple et al., 2014). Furthermore, the negative effects related to anthropogenic climate change produce uncertainty when planning biodiversity and carbon strategies (Klooster and Masera, 2000; Huston and Marland, 2003; Gibbs et al., 2007; Hanewinkel et al., 2013; Buizer et al., 2014). Therefore, studies of the relationships of forest vegetation to anthropogenic climate change present important interdisciplinary work in the subject areas of the biosphere, atmosphere, and anthroposphere.

China has large areas of forest vegetation that are critical to biodiversity and carbon storage (Zhang et al., 2000; Sayer et al., 2004; Peng et al., 2009; Piao et al., 2009). Studies have shown that past climate change shapes the current forest vegetation pattern in China, and anthropogenic climate change can force the variation of forest vegetation patterns in the future (Editorial Board of Vegetation Map of China, Chinese Academy of Sciences, 2001; Tian et al., 2011; Bruehlheide et al., 2014; Gao et al., 2016; Wang et al., 2017). Such variation may reduce terrestrial net primary production, alter forest structure and ecosystem function, and damage wildlife habitats (Fang et al., 2001; Iverson and Prasad, 2001; Peng et al., 2009; Tian et al., 2011; Bruehlheide et al., 2014; Gao et al., 2016). Yu et al. (2014) determined that subtropical forest vegetation contributes to a large carbon sink in China. Future climate change would decrease overall soil carbon across Chinese forest ecosystems (Peng et al., 2009; Tian et al., 2011). Chinese forest vegetation also provides abundant habitat types for many species; however, rapid climate change may increase habitat fragmentation and negatively impact habitat suitability for many species (Editorial Board of Vegetation Map of China, Chinese Academy of Sciences, 2001; Iverson and Prasad, 2001; Sayer et al., 2004; Clark et al., 2011). Wan et al. (2017) showed that dominant tree species of forest communities may be affected by climate change, and such effects can result in the species composition changes of forest vegetation in China. To avoid these types of negative outcomes related to anthropogenic climate change, it is urgent that biodiversity and carbon conservation strategies are based on vulnerability assessments of forest vegetation types throughout China (Klooster and Masera, 2000; Huston and Marland, 2003; Hanewinkel et al., 2013).

A number of vulnerability assessment approaches have been developed rapidly in response to the threat of climate change (Williams et al., 2007; Clark et al., 2011; Bellard et al., 2014; Ackerly et al., 2015; Pacifici et al., 2015; Rogers et al., 2017). Species–area relationship (SAR) is a theory commonly used to predict the number of vulnerable species potentially caused by climate change by reversing the species–area accumulation curve and extrapolating backwards to smaller areas to calculate expected species loss (Kinzig and Harte, 2000; Thomas et al., 2004; Williams et al., 2007; He and Hubbell, 2011; Bellard et al.,

2014). However, SAR may over-estimate species extinction (Kinzig and Harte, 2000). The relationship of the areal distribution of endemics within a habitat can decrease over-estimation of the extent of current species extinction, namely, endemics–area relationship (EAR; Kinzig and Harte, 2000; Bellard et al., 2014). The EAR is the relationship between the area of a region and the number of species limited (namely, endemic) to this region (He and Hubbell, 2011; Storch et al., 2012). Hence, the fundamental sampling is different between the SAR and EAR for the target species (He and Hubbell, 2011; Storch et al., 2012). Bellard et al. (2014) quantified the vulnerability of 34 biodiversity hotspots to anthropogenic climate change worldwide using the EAR approach. Watson et al. (2013) presented a measure of global ecosystem vulnerability based on spatial analysis of natural integrity, namely, the proportional area of intact natural vegetation habitats.

Species distribution modelling (SDM) is also an effective method to evaluate vegetation patterns across different spatial and temporal scales (Ullerud et al., 2016; Wang et al., 2017). Ullerud et al. (2016) used SDM to project the distributions of vegetation types in the boreal–alpine ecotone based on fieldwork and relevant explanatory climatic variables. Furthermore, SDM has been widely used in climate change studies. Previous studies have applied SDMs to evaluate the distributions of forest species using bioclimatic variables based on an equilibrium assumption that the natural distribution provides a reliable estimate of a species' climatic requirements (the earliest climate change studies in 1988; Hutchinson, 1957; Booth et al., 2014; Zhang et al., 2014; Wan et al., 2017; Wang et al., 2017). Long-lived tree species have a strong ability to control their sites, which can provide the climatic adaptability/plasticity in the potential distributions (Editorial Board of Vegetation Map of China, Chinese Academy of Sciences, 2001; Zhang et al., 2014; Wan et al., 2017; Wang et al., 2017). Forest communities are based on dominant tree species, and the equilibrium assumption could be used in the distribution projection of forest communities, which can provide the theoretical basis for the vulnerability assessment of forest vegetation to climate change using SDMs (Editorial Board of Vegetation Map of China, Chinese Academy of Sciences, 2001; Zhang et al., 2014; Wan et al., 2017; Wang et al., 2017). These studies provide the references for the planning of forest conservation management, and they give new insights into vulnerability assessment approaches for forest vegetation under anthropogenic climate change in China.

The primary objective of our study was to assess vulnerability of forest vegetation to anthropogenic climate change in China using SDM coupled with EAR. We examined 204 forest communities belonging to 16 forest vegetation types in China (Editorial Board of Vegetation Map of China, Chinese Academy of Sciences, 2001). We determined the current areas of forest communities based on past fieldwork data, and we used SDM to project future distribution areas. We then explored the important variables that influenced distribution areas of forest vegetation and quantified the vulnerability of forest vegetation to anthropogenic climate change based on EAR. Finally, we offer some suggestions on conservation management of forest vegetation in China.

2. Materials and methods

2.1. Current distribution areas of forest communities

The Chinese forest vegetation distribution data was compiled from the *Vegetation Atlas of China 1:1,000,000*; its 25,350 polygons of forest vegetation are based on data from robust field investigations (Editorial Board of Vegetation Map of China, Chinese Academy of Sciences, 2001; Zhang et al., 2007; Wang et al., 2017). We transferred the polygon data of forest communities into a $10 \times 10 \text{ km}^2$ grid map to obtain the current distribution areas of forest communities based on the network of grid cells (i.e., occurrence records; Wang et al., 2017). To produce useful predictions of SDM, we excluded forest vegetation types with <10 grid cells from this study (Shcheglovitova and Anderson, 2013). We identified 204 forest communities belonging to 16 forest vegetation

types (Fig. 1; Editorial Board of Vegetation Map of China, Chinese Academy of Sciences, 2001; Zhang et al., 2007); more detailed information is available in Table S1. We used forest communities as the basic units of forest vegetation in our study (Editorial Board of Vegetation Map of China, Chinese Academy of Sciences, 2001; Zhang et al., 2007). The forest communities are based on the dominant tree species, and we assumed that SDMs are theoretically built for these species (Ullerud et al., 2016; Wan et al., 2017; Wang et al., 2017).

2.2. Projecting future distribution areas of forest communities

We chose eight bioclimatic variables (detailed information in Table S2) and we used their current and future values to build SDMs. Eight current bioclimatic variables with 5.0-arc-minute spatial resolution (10×10 km grid) were downloaded from the WorldClim database (averages from 1950 to 2000 were used as current bioclimatic variables; www.worldclim.org; Hijmans et al., 2005) for the environmental input layers of the SDM (and the future bioclimatic variables; Table S2; Bellard et al., 2014). There were no multicollinearity effects in the parameter estimates of species distribution models (absolute Pearson correlation coefficients < 0.8). These eight bioclimatic variables were selected because they influence the distributions of forest communities (Editorial Board of Vegetation Map of China, Chinese Academy of Sciences, 2001; Ullerud et al., 2016; Wang et al., 2017). We relied on data from the Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report (AR5) to project future distribution areas of forest communities (www.ccafs-climate.org). To model the future distribution of forest communities in the 2080s (2071–2099), we used the average map of three global climate models (GCMs; i.e., cccma_canesm2, csiro_mk3_6_0, and mohc_hadgem2_es) and two greenhouse gas concentration scenarios, the Representative Concentration Pathways (RCPs) of 4.5 (mean: 780 ppm; range: 595 to 1005 by 2100) and 8.5 (mean: 1685 ppm; range: 1415 to 1910 by 2100), representing the low and high gas concentration scenarios, respectively (www.ccafs-climate.org; Bellard et al., 2014). RCP 8.5 has larger cumulative concentrations of carbon dioxide than RCP 4.5; thus, each scenario will cause

different climate changes due to variable anthropogenic concentrations of greenhouse gases and other pollutants (www.ccafs-climate.org).

Based on the equilibrium assumption of forest communities across different spatial and temporal scales, maximum entropy modelling, a common SDM, was used to project the future potential distribution areas of forest communities in China based on bioclimatic variables and occurrence records (Phillips et al., 2006; Ullerud et al., 2016; Wang et al., 2017). All grid cells were regarded as possible distribution space of maximum entropy (Phillips et al., 2006). We used MaxEnt software to run maximum entropy modelling using the current distribution data of forest communities as occurrence records (Ullerud et al., 2016; Wang et al., 2017). Map cells assigned a value of 1 had the highest scores of potential distribution probabilities, and those with a value of 0 had the lowest potential distribution probabilities (Phillips et al., 2006). The modelling sets were as follows: (1) the regularization multiplier (beta) was set to two to avoid model over-fitting (Radosavljevic and Anderson, 2014); (2) a tenfold cross-validation approach to remove the bias of occurrence records (Phillips et al., 2009; Merow et al., 2013); (3) the maximum number of background points was set to 10,000, which closely matched the empirical average distribution for each forest community, namely, close to the training data as far as possible (Merow et al., 2013); and, (4) the output format was cloglog (Phillips et al., 2017); all other settings were set as described in Ullerud et al. (2016). We used “10th percentile training presence threshold” to define distribution and non-distribution areas for all forest communities in the low and high gas concentration scenarios (Kramer-Schadt et al., 2013; Merow et al., 2013).

The significance of the percentage contribution (PC) of the bioclimatic variables, namely, their importance to distributions of forest communities, was then tested using the jackknife method (Oke and Thompson, 2015). We calculated the average PC based on 16 vegetation types. The important environmental variables for each vegetation type were considered to be ones with PC values higher than 15% (Oke and Thompson, 2015).

We used the area under the receiver operating characteristic curve (AUC) and training omission rate to assess model relative predictive

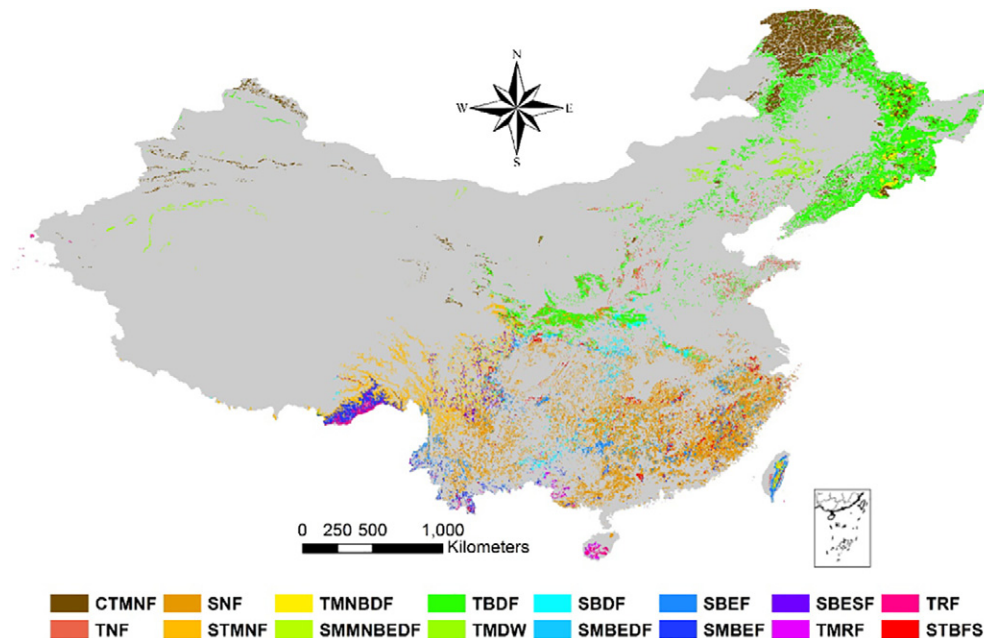


Fig. 1. Current distribution areas of forest vegetation. CTMNF: cold-temperate and temperate mountains needleleaf forest; SBDF: subtropical broadleaf deciduous forest; SBEF: subtropical broadleaf evergreen forest; SBESF: subtropical broadleaf evergreen sclerophyllous forest; SMBEDF: subtropical mixed broadleaf evergreen and deciduous forest; SMBEF: subtropical monsoon broadleaf evergreen forest; SMMNBDF: subtropical mountains mixed needleleaf, broadleaf evergreen and deciduous forest; SNF: subtropical needleleaf forest; STBFS: subtropical, tropical bamboo forest and scrub; STMNF: subtropical and tropical mountains needleleaf forest; TBDF: temperate broadleaf deciduous forest; TMDW: temperate microphyllous deciduous woodland; TMNBDF: temperate mixed needleleaf and broadleaf deciduous forest; TMRF: tropical monsoon rain forest; TNF: temperate needleleaf forest; TRF: tropical rain forest.

ability (Phillips et al., 2006). The range of AUC values varies from 0.5 (lowest predictive ability or not different from a randomly selected predictive distribution) to 1 (highest predictive ability; Phillips et al., 2006). Models of each species with values above 0.7 were considered useful in our study (Phillips et al., 2006). The training omission rate was the proportion of the training occurrence records placed in grid cells of predicted absence (Phillips et al., 2006; Anderson and Gonzalez, 2011). A low omission rate is a necessary condition for a good SDM (Phillips et al., 2006). We used a one-tailed binomial test for the null hypothesis that test points are predicted no better than those by a random prediction (Phillips et al., 2006; Anderson and Gonzalez, 2011). This yielded a binary prediction that includes all cells at least as suitable (according to the Maxent) as those where the species was known to be present (current distributions of forest communities; Phillips et al., 2006; Anderson and Gonzalez, 2011). The binomial probabilities were based on six thresholds (detailed information in Table S1; Phillips et al., 2006). A training omission rate with <17% was considered good for the model (Phillips et al., 2006; Anderson and Gonzalez, 2011).

2.3. Quantifying the vulnerability of forest vegetation to climate change

It is an important assumption that the limit of distribution areas can define the number of endemic species based on EAR (Kinzig and Harte, 2000; Williams et al., 2007; He and Hubbell, 2011; Bellard et al., 2014). Also, the relationship between the area of a region (i.e., the distribution ranges of forest communities) and the number of species restricted (i.e., endemic) to it was assumed in our study (Rosenzweig, 1995; He and Hubbell, 2011; Storch et al., 2012). Species endemic to certain climates are at risk of extinction, and communities may disaggregate or disappear if the climates disappear in those regions (Rosenzweig, 1995; Williams et al., 2007; Ullerud et al., 2016). Under this assumption, a loss of distribution areas of a forest community corresponds to a loss of habitat for endemic species (Rosenzweig, 1995; Kinzig and Harte, 2000; Williams et al., 2007; Bellard et al., 2014). Hence, the number of endemic species potentially threatened by climate change was evaluated by measuring the extent of the loss of distribution areas due to climate change using EAR (Kinzig and Harte, 2000; Bellard et al., 2014). We assumed the disappearing distribution areas, represented by the forest community range, were a proxy of the lost percentage of endemic species vulnerable to climate change (Williams et al., 2007; Bellard et al., 2014). We evaluated the lost percentage of endemic species to quantify the vulnerability of each forest community to climate change using the following equation (Kinzig and Harte, 2000):

$$S_{lost} = \left(\frac{A_{lost}}{A_{current}} \right)^{z'}$$

where S_{lost} is the degree of vulnerability of a forest community to climate change (the vulnerability index informs the proportional number of species that are expected to be locally extinct as the suitability area recedes with climate change); A_{lost} is the lost distribution areas with a forest community range under future climate change (current minus future distribution areas); $A_{current}$ is the 90% confidence limits of current distribution areas of the forest community range for reducing the bias and errors due to the scales of grid cells; and, z' is a constant [$z' = -\ln(1 - 1/2^z)/\ln(2)$]. Based on Bellard et al. (2014), we used an intermediate value of z (0.2) for our analysis because this value represents a balance between fragmented habitats and continental situations (Kinzig and Harte, 2000). A_{lost} values smaller than zero, or approximately zero, indicated the forest community type was not vulnerable due to climate change.

Finally, we computed the average lost percentage of endemic species of forest communities for each forest vegetation type to quantify the vulnerability of forest vegetation to climate change. The paired-samples t -test was used to evaluate the vulnerability difference between the low and high gas concentration scenarios. We divided the

vulnerability degrees (ranging from 0 to 1) into five levels, and calculated the occurrence of forest communities based on forest vegetation types across the levels. We used <20% of lost endemic species within the forest community as the indicator of relatively stable forest vegetation (Bellard et al., 2014).

3. Results

The modelling predictions were accurate with AUC larger than 0.7 and training omission rates smaller than 17% (one-tailed binomial tests: $P < 0.01$) across all forest communities (Table S1). Annual mean temperature, annual precipitation, and precipitation of driest month contributed to distributions of forest communities across all 16 vegetation types (Tables 1 and S3). Precipitation of driest month was the most important variable for the distributions of Subtropical broadleaf deciduous forest (SBDF; 60.7 ± 28.6) of all the variables and forest vegetation types (Tables 1 and S3).

Our analysis suggested that 78.9% and 61.8% of forest vegetation should be relatively stable in the low and high concentration scenarios, respectively (Fig. 2). There were large vulnerable areas of forest vegetation in northeastern and southwestern China in both low and high concentration scenarios (Fig. 3). Southeastern China had smaller areas of vulnerable forest vegetation (Fig. 3). With increasing gas concentrations, forest vegetation would become increasingly vulnerable (Fig. 3). In the high concentration scenario in particular, northwestern China would have several areas of vulnerable forest vegetation (Fig. 3).

Subtropical mixed broadleaf evergreen and deciduous forest (SMBEDF) was affected most severely in the low concentration scenario (vulnerability: 0.377; Table 2). However, vulnerability of forest vegetation of SMBEDF (vulnerability: 0.608), cold-temperate and temperate mountains needleleaf forest (CTMNF; vulnerability: 0.448), and temperate mixed needleleaf and broadleaf deciduous forest (TMNBDF; vulnerability: 0.628) types to climate change was greatly elevated in the high concentration scenario compared to the low concentration scenario (vulnerability: larger than 0.377; Table 2). Vulnerability was significantly higher in the high concentration scenarios ($P < 0.05$) for seven forest vegetation types, including CTMNF, TMNBDF, temperate needleleaf forest (TNF), subtropical and tropical mountains needleleaf forest (STMNF), temperate broadleaf deciduous forest (TBDF), subtropical broadleaf evergreen sclerophyllous forest (SBESF), and tropical monsoon rain forest (TMRF; Table 2). Climate change had the largest effects on forest communities including *Castanopsis orthacantha* forest (Subtropical broadleaf evergreen forest; SBEF), *Cyclobalanopsis glauca*, *Pistacia chinensis*, *Celtis sinensis* forest (SMBEDF), *C. glauca*, *Carpinus pubescens*, *Platycarya strobilacea* forest (SMBEDF), *Fagus lucida*, *Cyclobalanopsis myrsinaefolia* forest (SMBEDF), *F. lucida*, *Lithocarpus hancei*, *Illicium jiadifengpi* forest (SMBEDF), and *Pinus pumila* forest (CTMNF; Table S4).

4. Discussion

Our study used an integrated SDM and EAR approach to assess the vulnerability of forest vegetation to anthropogenic climate change in China, and we mapped the vulnerability of forest vegetation to climate change (Fig. 3). Our results showed that anthropogenic climate change is likely to pervasively affect forest vegetation in China. Such effects may be significantly enhanced with increasing greenhouse gas concentrations across seven forest vegetation types (detailed information in Tables 2 and S4). There would be areas of vulnerable forest vegetation in northwestern China in the high concentration scenario (Fig. 3). Furthermore, annual mean temperature, annual precipitation, and precipitation of the driest month were the most important environmental variables for the distribution areas of forest communities, which indicates that these three environmental variables should be used as the primary indicators for vulnerability assessments of forest vegetation under climate change (Table 1). We provide the references upon

Table 1
Importance of bioclimatic variables to the distributions of forest vegetation types.

Vegetation	Bio1 (%)		Bio4 (%)		Bio5 (%)		Bio6 (%)		Bio12 (%)		Bio13 (%)		Bio14 (%)		Bio15 (%)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
CTMNF	8.2	13.1	44.9	28.4	2.2	3.6	9.2	18.7	13.0	11.7	4.7	8.8	9.9	10.6	7.9	9.6
SDBF	2.8	2.8	10.0	6.6	2.9	2.6	3.8	4.2	10.3	13.8	6.2	16.3	60.7	28.6	3.4	1.8
SBEF	1.1	0.9	10.4	8.0	2.0	1.5	2.8	1.9	50.1	35.1	1.8	3.0	30.1	32.3	1.7	1.5
SBESF	6.5	7.4	25.3	10.5	1.4	1.2	6.7	9.5	46.2	26.3	1.2	0.9	8.0	5.5	4.7	3.2
SMBEDF	1.5	1.8	7.6	4.8	5.4	7.7	11.2	16.6	23.4	24.2	2.3	2.9	43.3	33.5	5.2	5.0
SMBEF	2.7	2.5	9.8	4.6	3.2	2.0	5.3	5.4	57.3	29.8	1.9	1.5	19.2	25.5	0.7	0.7
SMMNBEDF	2.4	1.5	13.5	11.8	6.1	2.8	6.4	7.3	47.4	24.3	1.9	3.0	18.6	14.7	3.7	3.7
SNF	2.2	2.0	7.4	5.7	2.7	2.7	4.3	3.2	45.3	34.0	1.6	4.3	33.0	33.8	3.5	4.4
STBFS	1.1	1.3	9.7	7.7	1.9	1.9	8.8	11.9	40.3	31.7	3.0	3.8	29.1	29.8	6.0	9.3
STMNF	2.3	2.3	12.9	7.1	8.0	9.1	2.9	2.9	60.1	21.5	2.8	6.4	7.0	6.0	4.1	5.9
TBDF	5.5	6.8	27.8	17.0	3.5	2.6	5.9	4.4	26.3	24.8	10.6	13.7	16.2	15.7	4.0	3.2
TMDW	11.9	21.3	60.7	28.3	2.1	1.9	4.7	3.6	4.0	8.0	14.8	13.4	0.5	0.4	1.3	1.4
TMNBDF	2.4	1.0	44.2	3.3	0.8	0.3	5.6	2.4	23.5	8.3	2.4	2.5	18.8	8.3	2.2	1.0
TMRF	2.1	1.5	15.1	6.3	1.0	0.9	10.3	10.1	45.8	27.5	3.8	3.6	19.1	15.0	2.6	2.5
TNF	3.2	1.8	11.6	9.0	6.0	2.1	14.2	6.8	20.5	14.1	13.4	19.5	26.6	21.9	4.4	3.5
TRF	2.5	4.2	19.6	12.1	2.7	4.0	6.3	3.1	38.3	25.9	11.6	8.8	16.4	20.0	2.5	1.6

The bold values represent the important variables to the distributions of forest vegetation types. Bio1: annual mean temperature; Bio4: temperature seasonality; Bio5: maximum temperature of the warmest month; Bio6: minimum temperature of the coldest month; Bio12: annual precipitation; Bio13: precipitation of the wettest month; Bio14: precipitation of the driest month; Bio15: precipitation seasonality. CTMNF: cold-temperate and temperate mountains needleleaf forest; SDBF: subtropical broadleaf deciduous forest; SBEF: subtropical broadleaf evergreen forest; SBESF: subtropical broadleaf evergreen sclerophyllous forest; SMBEDF: subtropical mixed broadleaf evergreen and deciduous forest; SMBEF: subtropical monsoon broadleaf evergreen forest; SMMNBEDF: subtropical mountains mixed needleleaf, broadleaf evergreen and deciduous forest; SNF: subtropical needleleaf forest; STBFS: subtropical, tropical bamboo forest and scrub; STMNF: subtropical and tropical mountains needleleaf forest; TBDF: temperate broadleaf deciduous forest; TMDW: temperate microphyllous deciduous woodland; TMNBDF: temperate mixed needleleaf and broadleaf deciduous forest; TMRF: tropical monsoon rain forest; TNF: temperate needleleaf forest; TRF: tropical rain forest.

integration of climate change into forest conservation management in China.

We delineated key regions with a high risk of vulnerability to climate change, particularly, northeastern and southwestern China (Fig. 3). Northeastern China has high forest species diversity and abundant forest resources, particularly large carbon stores (Zhang et al., 2007; Peng et al., 2009; Piao et al., 2009). Anthropogenic climate change poses a large potential threat to plant diversity and it could even affect the conservation functions of species diversity (McCarthy and Burgman, 1995; Reyer et al., 2014; Zhu et al., 2014; Wang et al., 2016). Temperature and precipitation changes can result in higher vapor pressure deficits and evaporation, and reduce the availability of water for plant growth (Beaumont et al., 2011). Furthermore, climatic variation could constrain the sizes of carbon pool and functional traits (e.g., cross-sectional area and biome of trees) related to ecosystem services (Wang et al., 2006; Hanewinkel et al., 2013; Buizer et al., 2014; Ripple et al., 2014). Our results indicated that forest vegetation in the eastern mountains of northeastern China was most vulnerable to future climate change (Fig. 3).

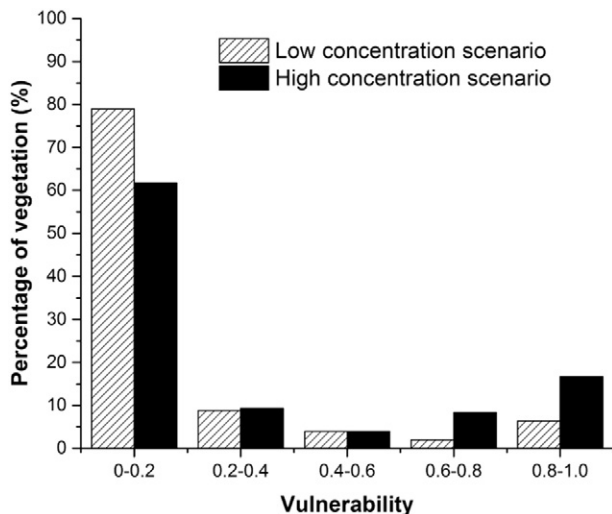


Fig. 2. Percentages of vulnerable forest vegetation due to climate change across five levels of vulnerability. Analysis includes 204 forest communities.

Intense human activities (e.g., excessive exploitation and utilization of wild resources, rapid urbanization) can decrease the size of viable species populations and their abilities to resist abiotic stressors (Klooster and Masera, 2000; Sayer et al., 2004; Jump and Penuelas, 2005; Traill et al., 2010; Hanski, 2015). Thus, anthropogenic climate change may enhance the negative effects on forest vegetation as a result of human influence (Jump and Penuelas, 2005; Traill et al., 2010; Hanski, 2015). Species diversity, carbon storage, and entire ecosystems may be severely negatively affected by anthropogenic climate change in northeastern China.

Southwestern China is a biodiversity hotspot; several species are threatened and even endangered (Myers et al., 2000; <https://www.iucn.org/>). Forest vegetation can provide suitable habitats for an abundant diversity of species and entire biomes (Olson et al., 2001; Buizer et al., 2014; Matthews et al., 2014; Hanski, 2015). However, increasing temperature can narrow suitable areas for particular forest types, especially in tropical biomes (Beaumont et al., 2011). Chinese conservation biologists and government managers have adopted a variety of conservation strategies to conserve and promote biodiversity in southwestern China (Zhang et al., 2012, 2014; Ren et al., 2016; Xu et al., 2017; Zhang et al., 2017). The network of nature reserves is increasingly being improved to conserve species diversity and increase habitat connections (Zhang et al., 2012, 2014; Xu et al., 2017). However, anthropogenic climate change is likely to weaken the effectiveness of conservation strategies and nature reserves for biodiversity because cold-temperate and temperate mountains needleleaf forest of southwestern China is especially vulnerable to climate change (Figs. 1 and 3; Table 2). Similar to our findings, other studies have shown that climate change has the potential to shrink distribution areas of forest species, change the composition of species communities, and lead to increased habitat fragmentation (Mawdsley et al., 2009; Araújo et al., 2011; Zhang et al., 2014; Wang et al., 2016). Chinese scientists have realized the importance of climate change to forest conservation in southwestern China; in particular, Yunnan Province has been extensively studied (Hu et al., 2008; Zhang et al., 2012, 2014; Ren et al., 2016; Zhang et al., 2017). For example, Zhang et al. (2014) used SDM to model the distribution pattern of forests in Yunnan Province, and they suggested that conservation policy should counter the predicted negative impacts of climate change on forest vegetation. Our study offers support to improve conservation policy for biodiversity, and improve the effectiveness of

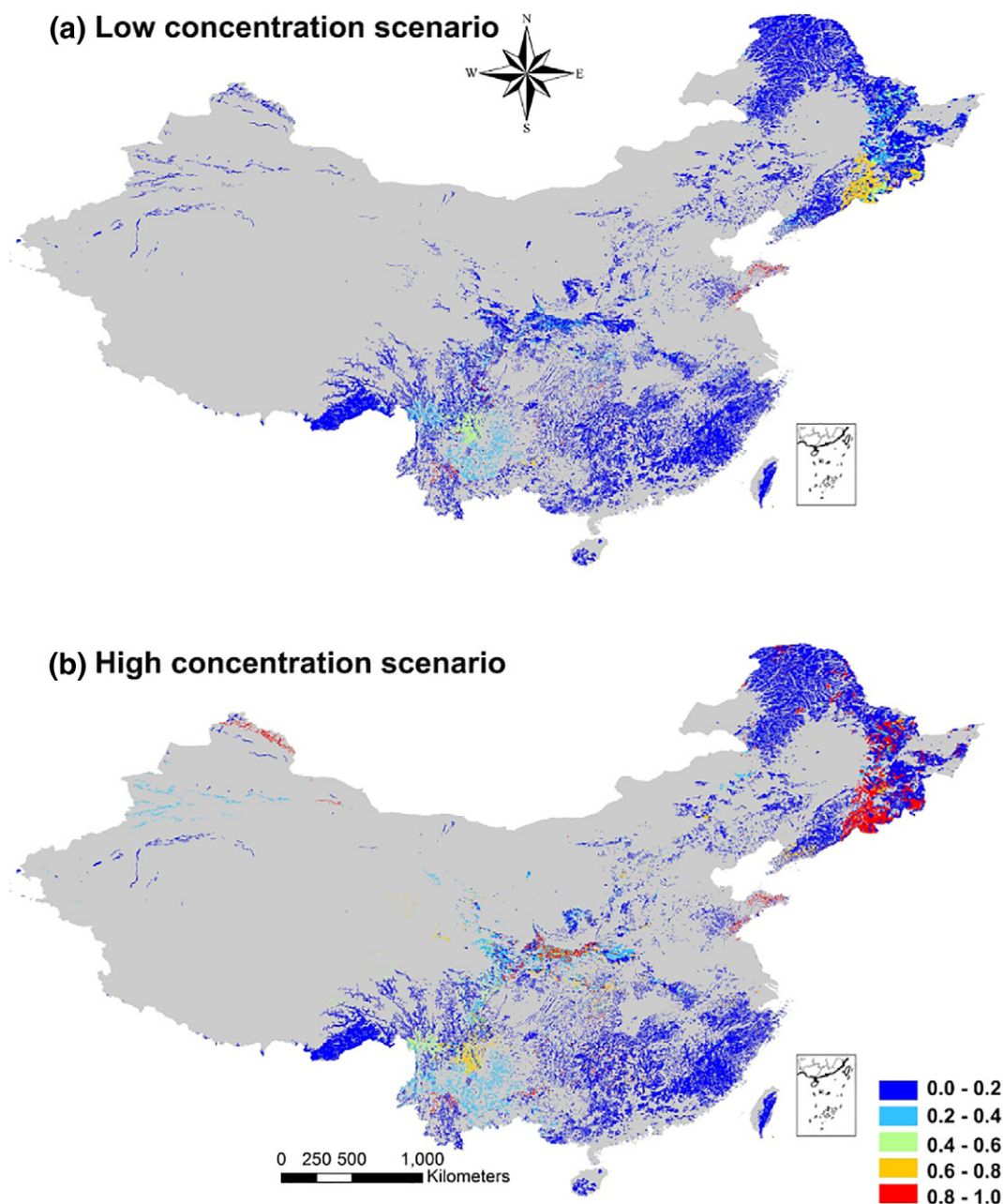


Fig. 3. Mapping the vulnerability of forest vegetation to anthropogenic climate change in China under low (a) and high (b) greenhouse gas concentration scenarios. Vulnerability of forest vegetation to climate change is indicated by blue to red colors to represent low to high vulnerability, respectively.

conservation strategies and nature reserve establishment in southwestern China.

Our study determined that the forest vegetation types most vulnerable to climate change included Subtropical mixed broadleaf evergreen and deciduous forest, Cold-temperate and temperate mountains needleleaf forest, and Temperate mixed needleleaf and broadleaf deciduous forest. Higher greenhouse gas concentrations could enhance vulnerability of these three forest vegetation types (Table 2). Vegetation of Subtropical mixed broadleaf evergreen and deciduous forest is one of the largest pools of primary productivity of China's terrestrial ecosystems, and it provides a variety of ecosystem services (e.g., climate, water, and nutrient regulations, food, raw materials, recreation, and refugium and nursery functions for animals and plants) for people (Dixon et al., 1994; De Groot et al., 2002; Piao et al., 2009; Yu et al., 2014). However, anthropogenic climate change may lead to the loss of important ecosystem services in the forests of this vegetation type (e.g., *F. lucida*,

C. myrsinaefolia forest; Table S4). More importantly, climate change may result in the extinction of species (Kinzig and Harte, 2000). Distribution area and number of species in vegetation types are largely related to precipitation (Bellard et al., 2014; Table 1). Hence, we suggest conducting extinction risk assessments for species considering precipitation changes in Subtropical mixed broadleaf evergreen and deciduous forest.

Our results that vegetation of Cold-temperate and temperate mountains needleleaf forest (e.g., *P. pumila* forest) was vulnerable to climate change indicated that species growth and composition within communities would shift because of climate change. Previous studies have shown that temperature limits the growth and reproduction of tree species more severely, and treeline expansion will be regionally variable in mountains needleleaf forests (Grace et al., 2002; Jump et al., 2009; Matías and Jump, 2012). Our results indicated that temperature seasonality was the most important variable to distribution areas

Table 2
Vulnerability assessment of forest vegetation to anthropogenic climate change in China.

Vegetation	Low concentration		High concentration		d.f.	P-values
	Mean	SD	Mean	SD		
CTMNF	0.101	0.222	0.448	0.424	21	0.000
SBDF	0.128	0.243	0.234	0.351	9	0.088
SBEF	0.164	0.320	0.238	0.345	14	0.022
SBESF	0.009	0.007	0.023	0.025	3	0.290
SMBEDF	0.377	0.413	0.608	0.423	18	0.007
SMBEF	0.009	0.011	0.064	0.092	4	0.258
SMMNBEDF	0.176	0.326	0.243	0.386	4	0.155
SNF	0.180	0.259	0.285	0.328	19	0.011
STBFS	0.058	0.096	0.100	0.265	12	0.496
STMNF	0.109	0.192	0.238	0.285	24	0.001
TBDF	0.089	0.162	0.341	0.364	31	0.000
TMDW	0.009	0.011	0.030	0.046	5	0.243
TMNBDF	0.308	0.223	0.638	0.404	5	0.011
TMRF	0.018	0.036	0.070	0.073	5	0.190
TNF	0.189	0.347	0.250	0.336	5	0.307
TRF	0.004	0.010	0.016	0.036	9	0.324

We tested (*d.f.* and *P*-values) the vulnerability between the low and high gas concentration scenarios for each forest vegetation type. Bold values represent the significant differences of vulnerability of forest vegetation to anthropogenic climate change between the low and high gas concentration scenarios ($P < 0.05$). CTMNF: cold-temperate and temperate mountains needleleaf forest; SBDF: subtropical broadleaf deciduous forest; SBEF: subtropical broadleaf evergreen forest; SBESF: subtropical broadleaf evergreen sclerophyllous forest; SMBEDF: subtropical mixed broadleaf evergreen and deciduous forest; SMBEF: subtropical monsoon broadleaf evergreen forest; SMMNBEDF: subtropical mountains mixed needleleaf, broadleaf evergreen and deciduous forest; SNF: subtropical needleleaf forest; STBFS: subtropical, tropical bamboo forest and scrub; STMNF: subtropical and tropical mountains needleleaf forest; TBDF: temperate broadleaf deciduous forest; TMDW: temperate microphyllous deciduous woodland; TMNBDF: temperate mixed needleleaf and broadleaf deciduous forest; TMRF: tropical monsoon rain forest; TNF: temperate needleleaf forest; TRF: tropical rain forest.

of mountains needleleaf forest vegetation, and those changes could result in increased vulnerability of forest vegetation (Table 1). Hence, temperature seasonality would be a preferred indicator to assess population changes in vegetation of Cold-temperate and temperate mountains needleleaf forest. Furthermore, Temperate mixed needleleaf and broadleaf deciduous forest vegetation are also widely distributed in northeastern China, the delineated risk regions in our study (Editorial Board of Vegetation Map of China, Chinese Academy of Sciences, 2001; Zhang et al., 2007). For conservation of species diversity, carbon storage, and ecosystems, we need to formulate adaptive conservation planning of climate change for the vegetation of Temperate mixed needleleaf and broadleaf deciduous forest in northeastern China (Huston and Marland, 2003).

We should also consider the inherent uncertainties associated with our analysis. First, the EAR of our study is a coarse estimation of species that are susceptible to being impacted in the future due to changes of *z*-values with different taxonomic groups; this may make it difficult to determine the vulnerability thresholds related to climate change (Kinzig and Harte, 2000; Bellard et al., 2014). However, our study only focused on the vulnerability degrees across different forest types, and that uncertainty was reduced as much as possible. Second, climatic niches are different for all species, resulting in various distribution areas. We used the jackknife method to evaluate the contribution of climatic variables to species distributions. We found that the distributions of most forest vegetation were related to annual mean temperature, annual precipitation, and precipitation of the driest month, thus, we could reduce the uncertainties related to climatic niches. Third, the analysis of future distributions was based on correlative SDMs, which have inherent uncertainties (Merow et al., 2013; Bellard et al., 2014). For example, some spatial biases of occurrence records may over- or underestimate potential distribution ranges (Merow et al., 2013). Furthermore, we mainly evaluated the vulnerability of forest vegetation to anthropogenic climate change in China based on the equilibrium assumption of forest communities across different spatial and temporal scales. Parts of

fundamental niches of forest communities could not be assessed in our study, which could result in SDM uncertainties. To decrease this uncertainty, we only assessed the future changes of distribution areas within current distribution ranges of forest vegetation, and used those changes to conduct the EAR analysis.

Despite these uncertainties, our assessments have profound insights for the conservation of forest vegetation. We highlight the urgency that climate change needs to be integrated into future planning of conservation policy for forests in China. We suggest improving the network of nature reserves, taking ex-situ conservation for threatened species in non-vulnerable regions, and prioritizing long-term monitoring of climate change in vulnerable regions (Araújo et al., 2011; Bellard et al., 2014; Ren et al., 2016). Further studies need to consider land-use changes and biological invasion for testing our study (Bellard et al., 2014). Moreover, mechanistic-SDM (mixed models) and trait-based vulnerability assessment approaches can improve assessments of vulnerability of forest vegetation to anthropogenic climate change in China (Pacifi et al., 2015). Finally, novel approaches need to be developed to address the issues of climate change and forest conservation.

5. Conclusions

We concluded that there are large areas of forest vegetation vulnerable to anthropogenic climate change in northeastern and southwestern China. Furthermore, vegetation of Subtropical mixed broadleaf evergreen and deciduous forest, Cold-temperate and temperate mountains needleleaf forest, and Temperate mixed needleleaf and broadleaf deciduous forest types would be affected most severely by anthropogenic climate change. Hence, we need to make climate-adaptive conservation strategies for forest vegetation in China. Annual mean temperature, annual precipitation, and precipitation of the driest month were the primary indicators of vulnerable forest vegetation under climate change. Our suggestion is to conduct the extinction risk assessment for species within forest vegetations considering different greenhouse gas concentration scenarios, with temperature and precipitation as indicators to assess forest vegetation population changes. Although there are some uncertainties with any such predictive analyses, our assessment provides important insights for planning of country-scale conservation management and establishment of nature reserves.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.scitotenv.2017.10.065>.

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